Capstone Project: Music Recommendation System

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1. Executive Summary

The project proposes the User-user similarity-based model for recommending top 10 songs for an established user of music recommendation system.
The core data used for the model is the Taste Profile Subset released by the Echo Nest as part of the Million Song Dataset, however it is suggested that the model should only consider a subset of the data (only users who listened to at least 90 or more songs and songs that have been listened by 120 or more users and only songs with max play count 5.)
The suggested model displays relatively high conformance with observed data and one of the lowest prediction errors (F1 score 52.5%, with Recall much higher than Precision, meaning that there’s a higher percentage of recommended songs that are relevant vs relevant songs that were recommended - almost 59% of recommended songs weren’t relevant).
However, it is subject to a number of limitations, including a lack of consideration for metadata like genre, type, mood or sonic analysis of the music/songs that could improve predictions as well as lack of measures for customer satisfaction (like customer retention vs engagement).
Also, environmental/time series data could be captured like the date, time of a day and year (seasonality), associated activity (relaxation, workout, work, cleaning etc.), location etc.
It is recommended that stakeholders consider these variables in building recommendation systems and think of better ways of measuring customer happiness with the product/predictions.

2. Problem and Solution Summary

2.1 Problem Summary

Recommendations Systems are one of the most profitable applications of data science in today’s world. Movies and music recommendations systems are especially popular. One of the examples is Netflix Recommendation Engine which value is reported as $1 billion per year and its viewer activity driven by personalized recommendations is around 80%.
The global music streaming market size grew from **$27.29** billion in 2022 to **$30.99 billion in 2023** at a compound annual growth rate (CAGR) of **13.5%.** It was expected to grow at **14.7%** annual growth rate from 2022 to 2030. Revenue forecast in 2030 is estimated to be **$103.07 billion**.
Spotify, YouTube Music, Pandora, SoundCloud, iHeartRadio, Tidal, Tidal, Apple Music, and Bandcamp are some of the most well-known digital music platforms in the market.
Spotify’s market cap is estimated at **$24.08 billion** (as of February 2023).

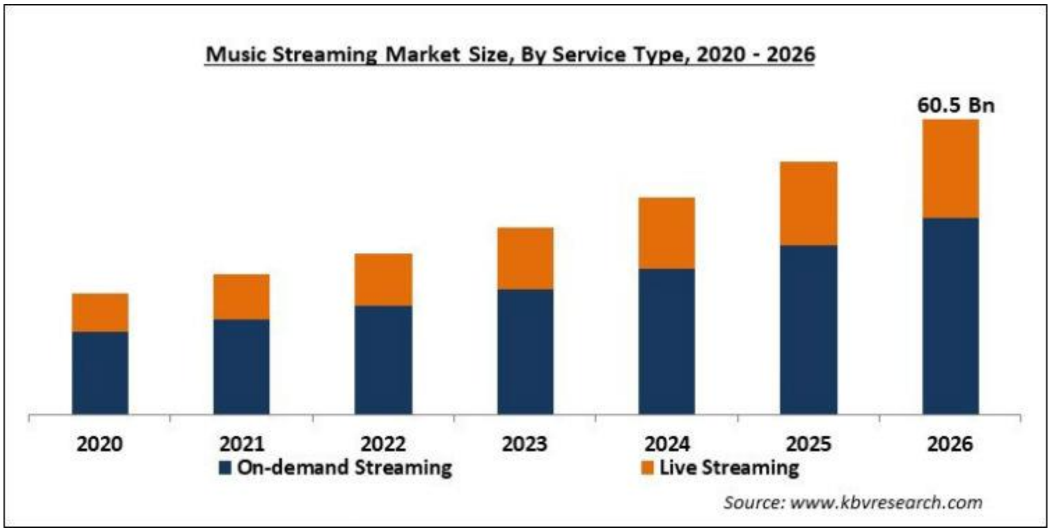

Figure 1: Music streaming market estimation forecast.

Some of the factors in market growth are rising use of smart devices and popularity of digital platforms.
Also rising use of 5G connectivity and cloud-based music leads to easier and more user-friendly experience (saving time-ease of use and money – for example on digital storage).

As the music recommendation market keeps growing, it is becoming increasingly important to keep high level of customer satisfaction (engagement and retention).

The key objective of this project is to build a recommendation system to propose the top 10 songs for a user based on the likelihood of listening to those songs in order to maximize their time spent on the platform.

The Recommendation Systems models presented here provide insight into different models and their hyper parameters, comparison of model evaluations, as well as predictions for relevant songs for a given user. The cold start problem will also be addressed.

The discussed analysis and predictions will help to understand the music recommendation process and models and serve as a basis for building more advanced models for future recommendation systems.

2.2 Solution design

A number of recommendation system models and methods were explored as part of the solution design, including popularity and content-based models, similarity-based models (user-user, item-item), matrix factorization and cluster-based models. The final proposed solution is the **user-user similarity-based model**, which has been optimized by **tuning values of the hyperparameters** using **grid search cross-validation.**

This model should only be used for established users though, for a "cold start", I propose using similarity or content-based model.
The table below presents all models and its evaluation measures.

User_id	Song_id	Perf eval measures	Similarity Based Collaborative Filtering				Model Based Collaborative Filtering		Cluster based Recommendation System	
			User - user		Item - item		Matrix Factorization			
			Baseline	Optimized	Baseline	Optimized	Baseline	Optimized	Baseline	Optimized
		RMSE	1.0878	1.0521	1.0394	1.0328	1.0252	**1.0141**	1.0691	1.0487
		Precision	0.396	0.413	0.307	0.408	0.41	**0.415**	0.398	0.397
		Recall	0.692	**0.721**	0.562	0.665	0.633	0.635	0.56	0.582
		F1	0.504	0.525	0.397	0.506	0.498	0.502	0.465	0.472
6958	1671	Pred1	1.801	**1.963**	1.361	1.963	1.267	1.343	1.294	1.294
6958	3232	Pred2	1.639	1.452	1.378	1.492	1.556	1.804	1.479	1.479
27018	1671	Pred3	1.275	1.286	2.551	2.337	2.217	2.264	2.403	2.403

Table 1: Model comparison.

Table above presents performance evaluation measures for few models (different algorithms, baseline model and optimized models – model after tuning hyperparameters).
It also shows predictions for a certain user and song, first one is for a known user-item interaction (actual value is 2) and last two are predictions for an unknows user-item interaction.

- As we can see from the table, the optimized models performed much better than the baseline ones.
- For all of the models Recall is much higher than Precision, meaning we're much better at recommending relevant songs than choosing relevant songs to be recommended (60-70% of songs that are recommended aren't relevant).
- This can cost us a lot.
- Two models that got my attention are **User-User Optimized Model for Similarity Based Collaborative Filtering** and **Optimized Model for Collaborative Filtering Matrix Optimization**.
- **Item-item Optimized Model for Similarity Based Collaborative Filtering** also performs well.

3. Recommendations for Implementation

3.1 Key recommendations for solution implementation

While talking about key recommendations for solution implementation, we need to mention limitations like **cold start problem**, meaning when a new user registers to the system or a new item is added to the library and system doesn't have enough information associated with these users/items. In this case, the system won't be able to recommend existing items to the new customer (new customer problem) or recommend a new item to the existing customer (new item problem). Another problem associated with the cold start is **sparsity** problem where there's not enough data in the system to make recommendation. Sparsity is the inverse of the ratio between given and possible ratings.

Because of those limitations, hybridization is well known approach in music recommendation systems.

Dividing users and songs into new and already existing and use of either popularity or context-based models (for new users or items) and user-user collaborative filtering models (for established users or items) seems like best approach.

Content based recommendation and cross-domain recommendation might solve the cold start problem.

In order to make the content-based recommendations possible additional data should be acquired about the users, songs and the interactions.

- Users – typical demographical data (age, geo location, education level, income, ethnicity), new user vs established user, free or paid membership.
- Songs – genre, type, sonic info (acoustic features including spectral properties, timbre, rhythm, and pitch).
- Interactions – seasonality (time of the year, time of the weekday), place (gym, plane, home- living room, entertainment, kitchen, bedroom, car, work), activity- can be tight to the place (resting/relaxing, working out, work, travel, cooking), time spent listening to the song (if the song was listened to till the end, stopped at 10%, 30%, skipped and how many times).

One on the methods to obtain additional information about the songs is automatic feature extraction from audio signals. It can be achieved by either extracting a feature vector from each item individually, independent of other items, or by considering the cross relation between items in the training dataset.
For more details about possible solution implementation and different approaches, please see [1].

3.2 Key actionable for stakeholders

Key actionable for stakeholders depend who the stakeholder is.
Music recommendation business is an example of managing several different stakeholders that are involved in delivering content.
Stakeholders:

- Music production companies
- Music Streaming Players
- Applications & Browsers
- App Stores
- Social media
- Company Website
- e-mail marketing
- pay-per click marketing

The primary stakeholders involved in the value chain are music creators & publishers, inbound content collection, software integrators, distribution channels, marketing & sales, and end-users.
Each stakeholder may have their own incentive to get their content in front of the end user and they may compete or collaborate with each other depending upon the context.
Music creators & publishers would want the most exposure and best customer experience (delivering the best possible song at the right time to the right end user) while the ad service is mainly interested in delivering the right ad to the right user at the right time.

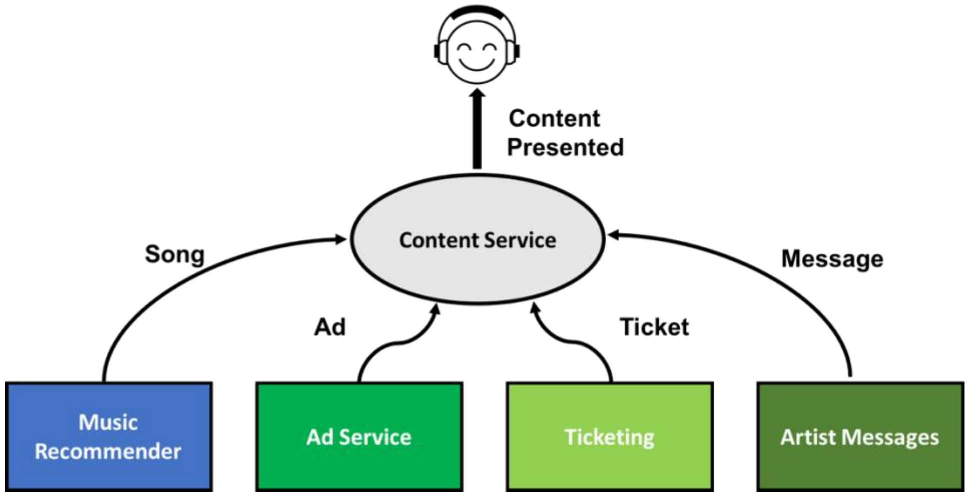

Figure 2: The architecture of a music recommendation platform consisting of multiple stakeholders.

Assuming that our stakeholder is Music Recommender, the key actionable would be to maximize user engagement and retention, which is highly correlated with customer satisfaction, therefore the main actionable should be to determine a way to measure customer happiness. There are many ways to determine customer satisfaction, I will analyze it in the next section.

3.3 Expected benefit and cost

The main benefit of good recommendation system is customer satisfaction (engagement and retention), ads, tickets, meaning happy user will bring profit.

The main cost of the recommendation system is the cost of creating and maintain the system including customer segmentation, frequency of recommendation and how many different models are used, cost of recommending songs that aren't relevant (in our case 58% of recommended songs weren't relevant which is very high cost).

3.4 Risk and challenges

The biggest challenge is to find the right songs for the right user. This task becomes hard without a clear user satisfaction measure. In our case we only had play count, so we assumed that the higher play count for a given interaction, the more satisfied user.
However, playing with threshold, I discovered that the best results (in terms of evaluation measures – precision and recall) is for threshold <1, meaning that recommended songs would have to be played only once before, not even (since on average, they would be played less than once).

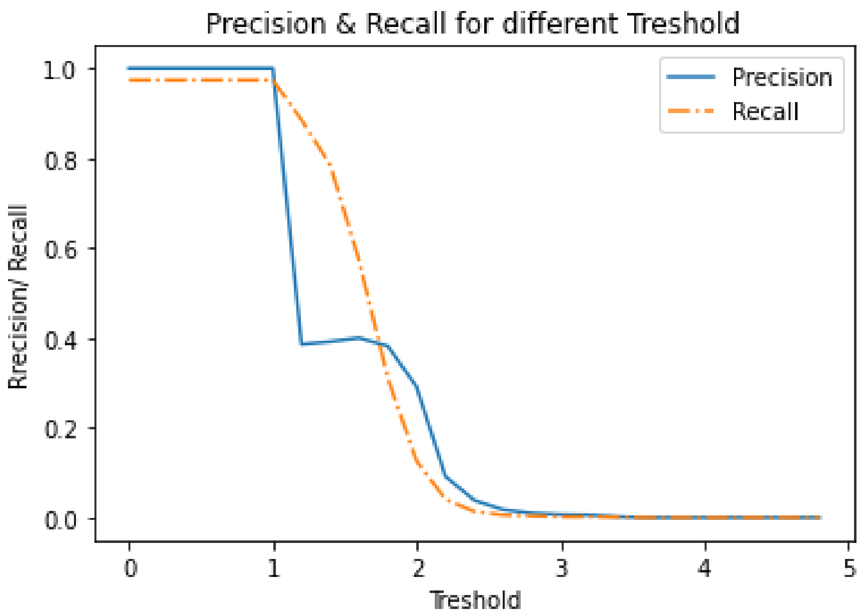

Figure 3: Precision@k & Recall@k for different threshold item-item base model/.

We already discussed cold start problem in previous sections.
Another challenge is Automatic playlist continuations.
Music recommendation systems come with its own set of particularities like

- Duration of items
- Magnitude of items
- Sequential consumption
- Recommendation of previously recommended items
- Consumption behavior
- Listening intent and purpose
- Emotions
- Listening context

Discussing all of above-mentioned particularities is outside the scope of the report, so we'll only focus on one - Recommendation of previously recommended items.
It is not clear to me if the listening to certain songs in an order has impact on the user. There are different sources with different opinion on this subject.
However, we know for sure that the mix of familiar and unknown songs was often mentioned as an important requirement for a good playlist. This discovery points us again toward the hybrid model between content-based and user-user similarity based collaborative filtering model.

Another big challenge in creating music recommendation system is its evolution. While evaluation of a model is pretty straightforward, using common model evaluation metrics (like RMSE, Precision@k, Recall@k and F1 score@k), user satisfaction isn't that straightforward.
Additional measures worth mentioning are

- Coverage - proportion of items over which the system is capable of generating recommendations
- Novelty –the ability to recommend new items that user haven't interacted with before
- Serendipity evaluates relevant and surprising recommendations
- Diversity gauges the extent to which recommended items are different from each other.

3.5 Further Analysis

Further analysis would consist of acquiring additional data mentioned previously (user, song and interaction data) and finding any dependencies (for example seasonality, time and place for an interaction, more context analysis for the songs and users).

Having richer data, different models could be applied like time series (seasonality) or neural networks.

Bibliography

- [1] Schedl M., Zamani H., Checn Ch., Daldjoo Y., Elahi M. 2018 Current challenges and vision in music recommender system research.
- [2] Abdollahpouri ,H. and Esisnger, S., 2017 Multiple Stakeholders in Music Recommender Systems.
- [3] Grand View Research, 2021 Music Streaming Market.

Appendix

Here are some recommendations for top 10 songs for a given user user_id 6958)

1. Popularity-based model

Recommend top 10 songs using the function defined above with min 50 interactions (number of play counts for a song):

1. 1.62 21 Back Against The Wall Cage The Elephant by Cage The Elephant from 2008
2. 1.49 22 Halo Doll Domination 3.0 by The Pussycat Dolls from 2008
3. 1.73 52 Halo Halo by Beyoncé from 2008
4. 1.73 62 You And Me Jesus Tribute To Jake Hess by Jake Hess from 2004
5. 1.45 93 I'm Still Breathing One Of The Boys (iTunes Exclusive) by Katy Perry from 2008
6. 1.61 97 Harder Better Faster Stronger Discovery by Daft Punk from 2007
7. 1.83 118 Bad Moon Rising The Complete Collection (Digital Box) by Creedence Clearwater Revival from 1969
8. 1.34 122 Phantom Part 1.5 (Album Version) A Cross The Universe by Justice from 0
9. 1.75 134 My Moon My Man My Moon My Man by Feist from 0
10. 1.74 139 I Got Mine Attack & Release by The Black Keys from 2008

2. Optimized User-user similarity based collaborative model

- 5 most recommended songs to the user number 6958 (based on user-user similarity based collaborative filtering):

1. 2.55 5531 Secrets Waking Up by OneRepublic from 2009
2. 2.52 317 Undo Vespertine Live by Björk from 2001
3. 2.41 4954 The Maestro Check Your Head by Beastie Boys from 1992
4. 2.4 8635 Una Confusion All Access by LU from 2006
5. 2.39 5943 You've Got The Love Lungs by Florence + The Machine from 2009
6. 2.39 1664 Horn Concerto No. 4 in E flat K495: II. Romanc... Mozart - Eine kleine Nachtmusik by Barry Tuckwell/Academy of St Martin-in-the-Fie... from 0
7. 2.35 6246 Canada The End Is Here by Five Iron Frenzy from 0
8. 2.32 1348 Mia First Love by Emmy The Great from 2007
9. 2.27 7496 The Gift We Don't Need To Whisper by Angels and Airwaves from 2006
10. 2.26 2852 West One (Shine On Me) The Crack/Grin And Bear It by The Ruts from 1980

3. Optimized item-item similarity based collaborative model

- This time our 5 recommended song for the user 6958 are (according to the recommendation predicted and corrected ratings):

1. 2.65 2342 Alaska If Looks Could Kill by Camera Obscura from 0
2. 2.39 5101 White Sky Contra by Vampire Weekend from 2010
3. 2.31 139 I Got Mine Attack & Release by The Black Keys from 2008
4. 2.27 7519 A Dustland Fairytale Day & Age by The Killers from 2008
5. 2.21 8099 Toxic The Singles Collection by Britney Spears from 2003
6. 2.17 2514 Big Big Love (Fig .2) Antidotes by Foals from 2008
7. 2.16 8304 The Way Things Go Identification Parade by Octopus Project from 2002
8. 2.15 4192 The Real Slim Shady Curtain Call by Eminem from 2000
9. 2.14 7295 This Is Your Life Day & Age by The Killers from 2008
10. 2.11 8704 Last Day Of Magic Midnight Boom by The Kills from 2008

4. Matrix factorization

- This time our 5 recommended songs to the user 6958 are (using Matrix Factorization models):

1. 2.6 7224 Victoria (LP Version) Hit By A Train: The Best Of Old 97's by Old 97's from 2006
2. 2.11 5653 Transparency Workout Holiday by White Denim from 2008
3. 2.01 8324 The Big Gundown Invaders Must Die Remixes and Bonus Tracks by The Prodigy from 2009
4. 1.92 614 You're The One If There Was A Way by Dwight Yoakam from 1990
5. 1.94 9942 Greece 2000 Greece 2000 by Three Drives from 1997
6. 1.9 5531 Secrets Waking Up by OneRepublic from 2009
7. 1.95 6450 Brave The Elements Brave The Elements - EP by Colossal from 0
8. 1.93 657 Luvstruck Hard House Anthems by Southside Spinners from 1999
9. 1.93 4831 Heaven Must Be Missing An Angel Capitol Gold: The Best Of Tavares by Tavares from 1979
10. 1.87 4811 Le Jardin d'Hiver Smile by Jacky Terrasson from 2002

5. Clustering

- This time our 5 recommended songs to the user 6958 are (using co=clustering

model):

1. 3.09 7224 Victoria (LP Version) Hit By A Train: The Best Of Old 97's by Old 97's from 2006
2. 2.31 8324 The Big Gundown Invaders Must Die Remixes and Bonus Tracks by The Prodigy from 2009
3. 2.22 9942 Greece 2000 Greece 2000 by Three Drives from 1997
4. 2.12 5531 Secrets Waking Up by OneRepublic from 2009
5. 2.09 1664 Horn Concerto No. 4 in E flat K495: II. Romanc... Mozart - Eine kleine Nachtmusik by Barry Tuckwell/Academy of St Martin-in-the-Fie... from 0
6. 2.12 4831 Heaven Must Be Missing An Angel Capitol Gold: The Best Of Tavares by Tavares from 1979
7. 2.07 6860 Mercy:The Laundromat Westing (By Musket and Sextant) by Pavement from 1993
8. 2.02 2220 Sehr kosmisch Musik von Harmonia by Harmonia from 0
9. 2.01 6246 Canada The End Is Here by Five Iron Frenzy from 0
10. 1.99 657 Luvstruck Hard House Anthems by Southside Spinners from 1999

6. Content based models

I checked user 6958 to see which songs he/she listened to the most, so we can use those songs to build the recommendations based on content-based model.

1. 5566 5 The Bachelor and the Bride Her Majesty The Decemberists by The Decemberists from 2003
2. 1050 5 Wet Blanket Old World Underground_ Where Are You Now? by Metric from 2003
3. 9351 2 The Police And The Private Live It Out by Metric from 2005
4. 3718 2 The Penalty The Flying Club Cup by Beirut from 2007
5. 1671 2 Sleeping In (Album) Give Up by Postal Service from 2003

- This time our 5 recommended songs to the user 6958 are (using content cased model)

Songs chosen based on Songs chosen based on 'The Bachelor and the Bride':

1. 447 Daisy And Prudence Distillation by Erin McKeown from 2000
2. 1674 I Need A Dollar I Need A Dollar by Aloe Blacc from 2010
3. 1936 Feel The Love In Ghost Colours by Cut Copy from 2008
4. 2716 All The Pretty Faces When You Were Young by The Killers from 2006
5. 3534 Who Let You Go? Sawdust by The Killers from 2007
6. 5095 Bones Bones by The Killers from 2006
7. 5715 Sam's Town Sam's Town by The Killers from 2006
8. 8624 Hearts On Fire Hearts On Fire by Cut Copy from 2007
9. 2914 Billy Liar Billy Liar (CD-Single) by The Decemberists from 2003
10. 6084 Red Right Ankle Her Majesty The Decemberists by The Decemberists from 2003

Songs chosen based on ‘Wet Blanket’:

1. 2107 Stadium Love Fantasies by Metric from 2009
2. 2289 Satellite Mind Fantasies by Metric from 2009
3. 2898 Twilight Galaxy Fantasies by Metric from 2009
4. 8037 Gold Guns Girls Fantasies by Metric from 2009
5. 9351 The Police And The Private Live It Out by Metric from 2005
6. 8138 Drop The World Drop The World by Lil Wayne / Eminem from 0
7. 2734 Love Me My Worlds by Justin Bieber from 2009
8. 3241 That Should Be Me My Worlds by Justin Bieber from 2010
9. 5843 You Give Love A Bad Name Slippery When Wet: Special Edition by Bon Jovi from 1986
10. 7224 Victoria (LP Version) Hit By A Train: The Best Of Old 97's by Old 97's from 2006